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Color Image Segmentation Based on Modified Kuramoto Model

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Abstract
A new approach for color image segmentation is proposed based on Kuramoto model in this paper. Firstly, the classic Kuramoto model which describes a global coupled oscillator network is changed to be one that is locally coupled to simulate the neuron activity in visual cortex and to describe the influence for phase changing by external stimuli. Secondly, a rebuilt method of coupled neuron activities is proposed by introducing and computing instantaneous frequency. Three oscillating curves corresponding to the pixel values of R, G, B for color image are formed by the coupled network and are added up to produce the superposition of oscillation. Finally, color images are segmented according to the synchronization of the oscillating superposition by extracting and checking the frequency of the oscillating curves. The performance is compared with that from other representative segmentation approaches.

Keywords: Kuramoto model, Neural Network, Color image segmentation

1 Introduction

Image segmentation is preliminary work for image feature extraction, and it is also a basic step toward computer vision. The quality of image segmentation affect directly the performance of the subsequent image analysis, therefore it is necessary and important to develop excellent image segmentation approach in order to obtain high quality of analysis.

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Mammals have very complex visual system, which can segment images at a glance. However it is difficult for any machine to do this job, no matter how efficient and developed it is. Simulating the visual system of mammals is promising to solve the natural image segmentation problem, therefore the activity mechanism of visual system have come to notice both for neuroscience and artificial intelligence. As the neuron activity in visual cortex and retina determines the behavior of the visual system, a lot of experiments have been done to investigate the activity of neurons in the visual cortex and retina of cats and monkeys, and a general conclusion is that the elementary activity of cerebral cortex neurons is oscillation [1]. In the early 1950s, models have been built to simulate the behavior of a single neuron. The most famous one is Hodgkin-Huxley model [2]. Hodgkin and Huxley used four differential equations to describe the membrane potential change by the flow of sodium, potassium ion current and the leakage current (mainly of Cl-ions), through which the neuron activity of oscillation is well explained. Although the Hodgkin and Huxley model (H-H model) is very close to the dynamics of the real neuron, the equations of this model are very complex, and it is almost impossible to obtain analytical solution, therefore it is difficult to analyze the neuronal activity analytically. With the discovery of the existence of synchronous firing in visual cortex and in different areas of the brain [3], building simpler models to simulate the periodic activity of single neuron is becoming important for the purpose of usage. In 1961, FitzHugh [4] simplifies the H-H model to simulate the complex neuronal electrical activity, in which a recover variable is introduced to replace the description for the ion flow and a two-variable FHN model is built by reducing the dimension to two. Later, another two-variable differential equation model: Wilson-Cowan oscillator model [5] is built by introducing a sigmoid function to describe the rate of change of the membrane voltage. Limit cycles generated from the above three models are generally used to simulate the periodic activity of cortex neuron. However, the generation of limit circle is influenced by the input of the system. If the input results in disappearance of limit cycles, the usage is restricted especially when the interaction between the neurons are considered. In this paper, a phase change dynamical model is introduced and the neuron activities are reconstructed to simulate the periodic activity in order to avoid the disappearance of limit cycles.

Based on single neuron activity simulation, neuron network models have been developed to simulate the behavior of a large set of coupled neuron oscillators. In 1989, oscillation synchronization [6] of visual cortex neurons is found by experiments, and it induces great interest to neuroscience. It is found that biological systems use oscillation synchrony of cortex neuron to implement visual functions. Through stimulus forced and stimulus induced synchronization, pulse coupled neural networks cause neurons with similar inputs to fire together, which can be used in image segmentation. In order to explore the usage of neuron synchronization to deal with the problems in image perception, Wilson-Cowan oscillator network model is built and investigated [6-8] and the chaotic synchronization conditions of the network are given. It had been used in gray image segmentation. By introducing two kinds of neurons (one is excitatory and the other is inhibitory), local stimulation and global inhibition mechanisms, Wang proposed the LEGION model [9] to simulate the visual cortex and apply it to gray image segmentation by using the synchronization principle. Ursino [10] and his colleagues make successive research based on the work of Von der Malsburg and Wang [11, 12], they used constant synapses for local connections and suggest a contour information inhibited mechanism for image segmentation. However, only white-black image segmentation problems are solved by the model. In this paper, by introducing instantaneous frequency, a phase dynamical model is built for coupled neurons and the activity is reconstructed. By the superposition of oscillating curves corresponding to RGB color information, color images are segmented in the form of oscillation. An approach to extract and check the features of synchronization are given, and a color image segmentation method is proposed and used for natural image segmentation.

The paper is organized as follows. In Section 2, the modified Kuramoto model is described. In Section 3, the analysis and application of the proposed model is given. In Section 4, simulation experiments for image segmentation are conducted and the performance is compared with other methods' segmentation results. Section 5 gives the conclusions.

2 Mathematical model

The Kuramoto model [13], first proposed by Yoshiki Kuramoto, is a mathematical model used to describe synchronization. It is a model for the behavior of a large set of coupled oscillators. Its formulation is motivated by the behavior of systems of biological oscillators, In this model, the coupling strength among the oscillator is represented by the phase difference. The original Kuramoto model [14] is as follows:

$$\dot{\theta}_i = \omega_i + \sum_{j=1}^{N} \Gamma_{ij}(\theta_j - \theta_i) \qquad i = 1, \cdots\cdots, N \tag{1}$$

where θ_i is the phase of oscillator i, N is the total number of oscillators, ω_i is the natural frequency of the oscillator, and Γ_{ij} acts as the role of the mutual coupling between oscillators, and the oscillators are globally coupled. The form of Γ_{ij} is as follows:

$$\Gamma_{i,j}(\theta_j - \theta_i) = \frac{K}{N}\sin(\theta_j - \theta_i)$$

The rhythmicity activity of each oscillator may be due to internal processes or to external stimuli, and the exact mechanism is neglected in this model, as well as external sources acting on the internal process. However, this phenomenon model correlates both the inner rhythmicity of each oscillator and the effects of other oscillators in its environment. As each element has a natural frequency, thus each oscillator tries to run independently at its own frequency while the coupling tends to synchronize it to all the others. The original analysis of synchronization by Kuramoto [14] deals with equation (1) in the case of mean-field coupling. An order parameter is defined and used to measure oscillator synchronization. The order parameters are the average of frequencies and phases. He found that the oscillators rotate at the angular frequencies given by their own natural frequencies if the coupling approaches zero. The oscillators become synchronized to their mean phase if the coupling strength is strong enough to exceed a critical value. For intermediate couplings, part of the oscillators are phase-locked and part are rotating out of synchrony with the locked oscillators. The synchronization in the mean-field case is revealed by a non-zero value of the order parameter. However the concept of order parameter as a measure of synchronization is less useful for models with short range coupling. More complex situations can occur in the system with short-range coupling, for example, a fraction of oscillators can change at the same speed, while different oscillator groups have different speeds.

One natural extension of the original Kuramoto model is to consider short- range interaction effects, and the other one is to add external fields that can model the external current applied to a neuron so as to describe the collective properties of an excitable system. We extend the Kuramoto model from these two directions to simulate the response of visual neurons to external image stimulation. Firstly the Kuramoto model is modified from global coupled interaction to local coupled ones and we build the mapping dynamic model to obtain the discrete frequency. By differentiating formula (1) we have:

$$\ddot{\theta}_i(t) = \sum_{j=1}^{N} \dot{\Gamma}_{i,j}(\theta_j(t) - \theta_i(t)) \tag{2}$$

Discretize (2) about t, we have

$$\dot{\theta}_i(t+1) = \dot{\theta}_i(t) + \sum_{j=1}^{N} \dot{\Gamma}_{i,j}(\theta_j(t) - \theta_i(t)) \tag{3}$$

Let

$$\dot{\Gamma}_{i,j}(\theta_j-\theta_i)=\begin{cases} a_i(\dot{\theta}_j-\dot{\theta}_i) & |\dot{\theta}_j-\dot{\theta}_i|<d_1 \\ 0 & |\dot{\theta}_j-\dot{\theta}_i|\geq d_1 \end{cases} \tag{4}$$

where $a_i=\dfrac{b}{m_i}$, $A_i=\{\theta_j \,\|\, \dot{\theta}_j-\dot{\theta}_i|<\mathrm{d}_i\}$, m_i is the number of neurons with frequency in set A_i, 0<b<1.

If there are only two oscillators, and $\left|\dot{\theta}_1(0)-\dot{\theta}_2(0)\right|<d_1$, after a period of time, the instantaneous frequency of oscillator 1 and oscillator 2 will be equal by the coupling strength of (4) through (3). If $\left|\dot{\theta}_1(0)-\dot{\theta}_2(0)\right|>d_1$, the instantaneous frequency of oscillator 1 and oscillator 2 will never be equal as there is no pulling strength between them. Kuramoto uses formula (1) to investigate the conditions that result in synchronization and the degree of the corresponding synchronization. Here we just analyze the synchronization caused by external stimuli under fixed coupling parameter, and we only focus on frequency synchronization. Some related definitions are as follows:

Definition 1. If $\dot{\theta}_j=\dot{\theta}_i$, the oscillator i and j are in frequency synchronization, and if $\lim_{t\to\infty}(\dot{\theta}_j-\dot{\theta}_i)=0$ the oscillators i and j are approaching frequency synchronization.

By definition 1, when a group of neurons are in synchronization state, they have the same or almost the same frequency. Here we use the phase changing rate equation to simulate the activity of human visual cortex neurons, in fact, phase changing rate is instantaneous frequency, therefore we use f_i to replace $\dot{\theta}_i$ ($f_i(t)=\dot{\theta}_i(t)$), and take average frequency to replace the individual neuron coupling, then Eq. (3) is changed to the following iteration equation

$$f_i(t+1)=f_i(t)+m(\overline{f}_i(t)-f_i(t)) \tag{5}$$

where $m(\mathrm{x})=bx$, $\overline{f}_i(t)$ is the average frequency of the oscillators in set A_i, and neurons only couples with a set of other neurons that has not very much large frequency difference with them.

Definition 2. Suppose that the activity of a single neuron is given as $\psi=A\cos(g(t))$, and A is amplitude, t is time, the instantaneous frequency is defined as $f(t)=\dfrac{g'(t)}{2\pi}$.

By definition 2, if $g(t)=\alpha t+\beta$, and $\psi=A\cos(\alpha t+\beta)$. Then we have $f(t)=\dfrac{\alpha}{2\pi}$, this is in accordance with the physical meaning of frequency.

Based on the above analysis and definition 2, if it is assumed that the initial phase of each neuron is 0, according to equation (4) we can reconstruct the neuronal activity as follows

$$\varphi_{i,j}(t+1)=A\cos[(f_{i,j}(t)+m(\overline{f}_{i,j}(t)-f_{i,j}(t))2\pi t] \tag{6}$$

Now that we have rebuilt the neuron activity with short-range neuron interaction, we take the pixel values of images as external stimulation. In order to analyze the neuron response for images, we introduce the topology of the neuron network as follows in fig.1 and fig.2. (i,j) indicates the i th row and j th column in the two dimensional grid, $1\leq i\leq M$, $1\leq j\leq N$, M,N corresponds to the input image size of the network. $\varphi_{i,j}(t+1)$ denotes the neuron activity in i th row j th column at time step $t+1$, $f_{i,j}(t)$ is the instantaneous frequency at time t. $\bar{f}_{i,j}(t)$ denotes the average instantaneous frequency of the local neuron oscillators connecting to neuron $a_{i,j}$, and $a_{i,j}$ denotes the neuron at position (i, j). The meaning of $\bar{f}_{i,j}(t)$ here is a bit different from the meaning of the $\bar{f}_i(t)$ in formula (5), and neuron $a_{i,j}$ only couples to its nearest neighbor in the grid shown in Fig. 1. Then the model is changed to be a local coupled network model in two-dimension space. $m(\bar{f}_{i,j}(t)-f_{i,j}(t))$ denotes the frequency change of neuron $a_{i,j}$ induced by the local neighbors from time t to $t+1$. The neuron is connected at most to its eight immediate neighbors except for those on the boundaries whose neighbors are less than eight.

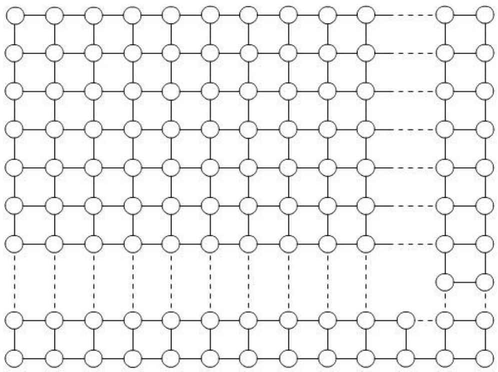


Figure 1: The connection topology of the network.

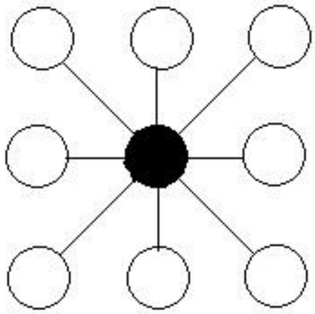


Figure 2: The sketch of local coupling neurons.

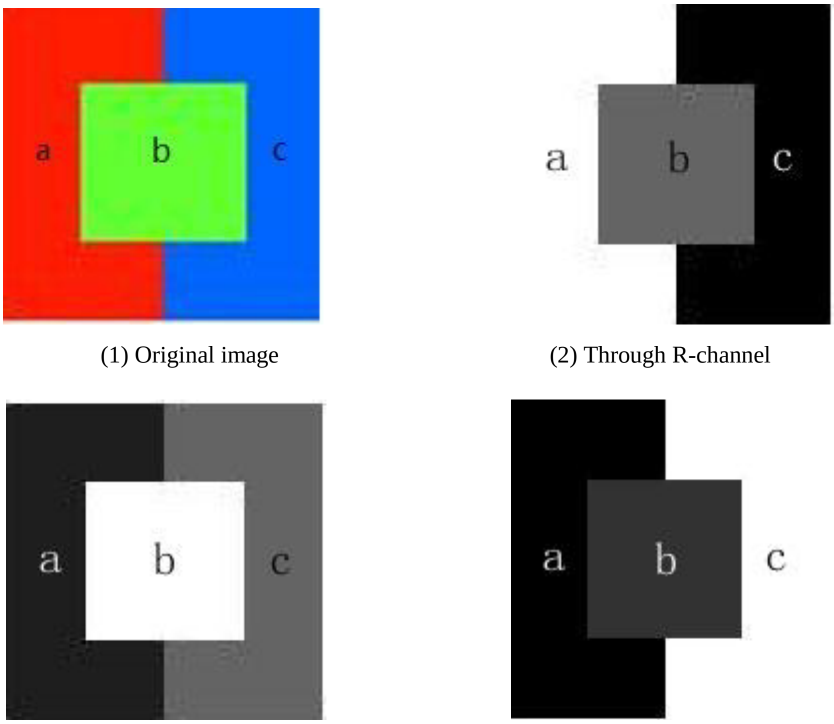
3 Application

Perception is an old fascinating and unsolved neuron-physiological problem that has attracted the attention of many neuroscientists for decades. Visual cortex is an important sensory processing place and neurons that detect features are distributed over different areas of the visual cortex. These neurons process information from a restricted region of the visual field and integrate it to create a complete representation of a given object through a complex dynamical process that allow us to detect object, separate them from the background, identify their characteristic, etc. All these tasks give rise to cognition and simulating the sensory processing is important not only for neuroscience but also for artificial intelligence.

Facing lots of visual information, the visual system receives and mixes them together using a special inner mechanism (we think oscillation Superposition is one). Such information includes color, edge, space location etc. Then the mixed information are input to the high layer of the mammal cortex, and neurons in different areas of the cortex process the information and decompose again into color, edge, space location etc. However in this paper, only simple information, such as R, G, B (red, green and blue) colors, is considered.

In this section, we use the network model to deal with the image segmentation problem. Firstly the pixel of each image is represented in the form of oscillation, and then a frequency extracting approach is developed to identify the frequency of the oscillating curve corresponding to each pixel of the input image following the mechanism of hearing. We choose the group of neurons that has the same frequency correspond to one object. Each pixel in the image corresponds to a neuron of the network. The connection between neurons is illustrated in Fig. 1, in which circles represent neurons, and each neuron receives information from its eight neighbors. With the values of pixels putting into the network system, the neurons in the network will oscillate with time following the corresponding dynamic equations. If some of the neurons approaches synchronization, we say these neurons belong to the same class and the corresponding pixels have same characteristics, and they can be put into the same area, following this principle the image can be segmented.

For any color images, each pixel consists of three primary colors R,G and B, let the color images go through R, G, B three-channel filters, then three single gray-scale images are formed and shown in Fig. 3. For the three single gray-scale images, the pixel values are extracted and put into the network respectively. Step by step, computing Eq. (5) iteratively, we get instantaneous frequency for each pixel value in the three single gray-scale images respectively. Then following Eq. (6), the activity of each neuron is rebuilt. For each pixel in the original color image, three activity curves are formed and in Fig. 4 the corresponding oscillating curves are given for different parts of the original image of Fig. 3(1).



(1) Original image (2) Through R-channel

(3)Through G-channel (4) Through B-channel

Figure 3: Original color image and three single gray-scale images through three channels (white regions).

In order to find out the characters that label the different parts of the color image, the three oscillations are summed up as follows:

$$\varphi_{i,j}(t)=\varphi_{r,ij}(t)+\varphi_{g,ij}(t)+\varphi_{b,ij}(t)$$

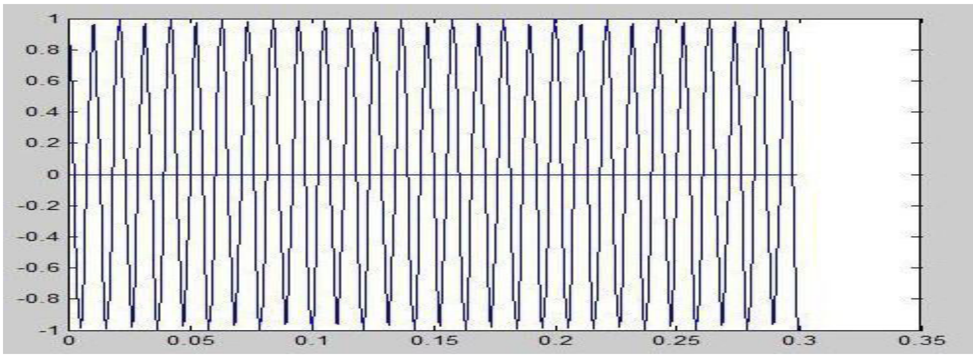
where $\varphi_{r,i,j}(t+1)=A\cos[(f_{r,i,j}(t)+m(\overline{f}_{r,i,j}(t)-f_{r,i,j}(t))2\pi t]$,

$\varphi_{g,i,j}(t+1)=A\cos[(f_{g,i,j}(t)+m(\overline{f}_{g,i,j}(t)-f_{g,i,j}(t))2\pi t]$,

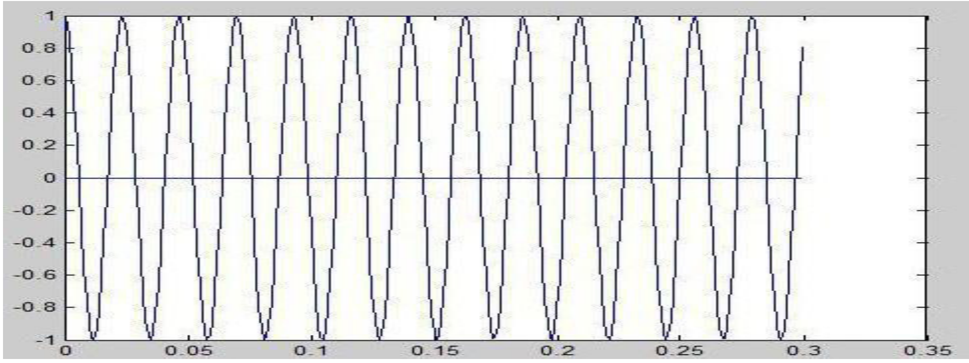
$$\varphi_{b,i,j}(t+1) = A\cos[(f_{b,i,j}(t) + m(\overline{f}_{b,i,j}(t) - f_{b,i,j}(t))2\pi t]\,.$$

We intend to use the "harmonic rhythm" to describe the information of different parts of the color image. The uniqueness of the Fourier transform shows that signals and their spectrums are one to one. Fourier transform is another expression of signals, and any periodic signal can be expanded to Fourier series. The term of the Fourier series is the sine or cosine signal with different frequencies. A periodic signal can be regarded as the signal (harmonic rhythm) superposition, and a non-periodic signal can be regarded as a periodic signal whose period tends to infinity. Certainly the periodic signal can be decomposed to its harmonic rhythms, and by superposing different harmonic rhythms, we can obtain the expected signal information. Therefore, the superposition of oscillations corresponding to R, G and B is unique following the uniqueness of Fourier transformation.

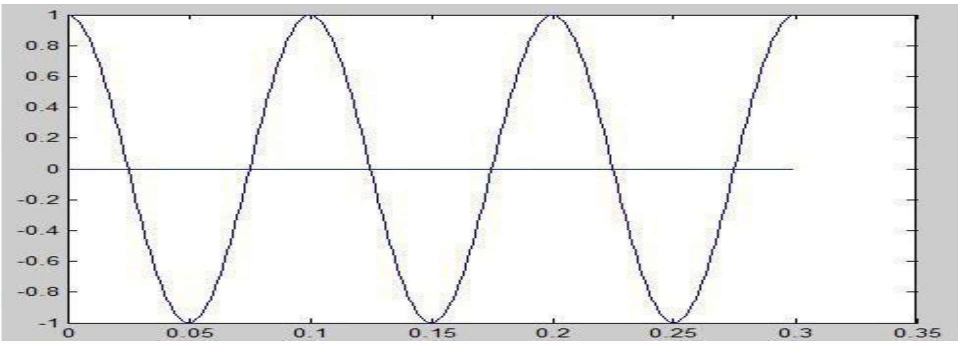
Extracting the pixel values point by point from the single gray-scale image (2), (3) and (4) in Fig. 3 respectively, we use $I_{i,j}$ to denote the pixel value, and normalized it to be $I_{i,j}/3+10$ which acts as the input into the neuron network at the initial time. According to the synchronization of neurons, it is regarded that neurons having the same activity correspond to the same object; different neuronal activity curves represent different areas of the image. If, however, the model is sensitive to noise or the frequency of natural images is difficult to distinguish, we take the "lower–right-synchronization" principle to adjust the frequency of neuronal activity for the robust to noise. The principle is: if the changing level corresponding to neuron (i, j) is zero and the neuron frequencies in the neighborhoods are close and not equal, the frequency of the neuron (i, j) is changed to equal to the frequency of the neuron (i+1, j+1). If the frequencies of the neuron (i+1, j+1) and neuron (i, j) are not close and the frequencies of the neuron (i+1, j) and neuron (i, j) are close , the frequency of the neuron (i, j) will be changed to be equal to the frequency of the neuron (i+1, j). Considering the neurons in turn $(i, j-1)$, $(i, j+1)$, $(i+1, j-1)$, $(i-1, j+1)$, $(i-1, j)$, $(i-1, j-1)$, the degree of the closeness depends on the threshold d_1. If the frequencies of all the neurons in the neighborhood of neuron (i, j) are not close to the frequency of the neuron (i, j), we change the frequency of the neuron (i, j) to be equal to the frequency of a neuron in the neighborhood. The oscillation curve of each neuron is different because of different input at the beginning. As time goes on, the coupling strength between one and another will pull some neurons together as one feature group. We use the different groups to segment the different areas of the image.



(i) The curve of the activity of the neuron corresponding to region a in Fig. 3(2).



(ii) The curve of the activity of the neuron corresponding to region b in Fig. 3(3).



(iii) The curve of the activity of the neuron corresponding to region c in Fig .3(4).

Figure 4: The curves of the activity of a neuron in Fig. 3(2).

Once the superposition curves are obtained, we propose an approach to classify them to different groups. Suppose that the superimposed oscillation is $f(t)$ and $f(t)=A_1\cos 2n'\pi t+A_2\cos 2n''\pi t+A_3\cos 2n'''\pi$, A_1, A_2, A_3 denotes the amplitudes of the neurons corresponding to R,G,B. n',n'',n''' denote the frequency of the neurons corresponding to R,G,B and $n',n'',n'''\in[10,255]$. The closed interval $[10,255]$ consists all the γ oscillating bands.

We compute the inner product of $f(t)$ and $\cos 2\pi nt$ in $L^2(R)$ space, where n acts as both a variable and an integer, $n\in[10,255]$,

$$\int_0^1 f(t)\cos 2\pi n t dt=\int_0^1\left(A_1\cos 2n'\pi t+A_2\cos 2n''\pi t+A_3\cos 2n'''\pi t\right)\cos 2n\pi t dt \qquad (7)$$

A program is developed to compute Eq. (7) by increasing 1for each step and iteration, we consider the following different situations:

1. While n',n'',n''' are different from each other and the difference is very big. As n',n'',n''' are all integers, suppose that $n'<n''<n'''$. With n changing from 10 to 255, we have the three cases:

If $n=n'$, (7) is changed to, $\int_0^1 A_1\cos 2n'\pi t\cos 2n\pi t dt=\frac{A_1}{2}$

And if $n=n''$, or $n=n'''$, (7) is changed to

$$\int_0^1 A_2\cos 2n'\pi t\cos 2n\pi t\,dt = \frac{A_2}{2},$$

and $\int_0^1 A_3\cos 2n'\pi t\cos 2n\pi t\,dt = \frac{A_3}{2}$, respectively,

the corresponding frequencies are known in this way when (7) is changed to $\frac{A_1}{2}, \frac{A_2}{2}, \frac{A_3}{2}$.

2. If there are two of n', n'', n''' that are close. Without loss of generality, we might as well suppose n' is close to n''. With n changing from 10 to 255, if $n = n' = n''$ occur, (7) is changed to

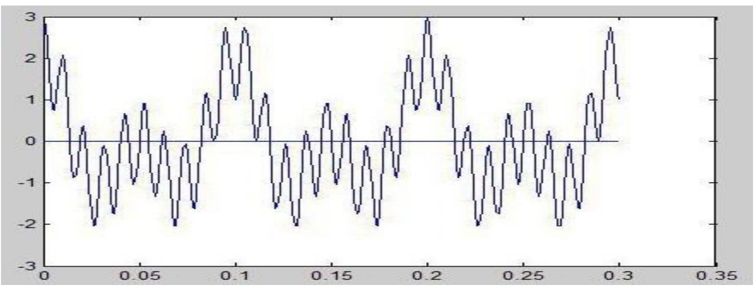
$$\begin{aligned}
&\int_0^1 (A_1\cos 2n'\pi t + A_2\cos 2n''\pi t)\cos 2n\pi t\,dt \\
&= A_1\int_0^1 \cos 2n'\pi t\cos 2n\pi t\,dt + A_2\int_0^1 \cos 2n''\pi t\cos 2n\pi t\,dt \\
&= \frac{A_1}{2} + \frac{A_2}{2}
\end{aligned}$$

If $n = n'''$ occur, (7) is changed to $\int_0^1 A_3\cos 2n'\pi t\cos 2n\pi t\,dt = \frac{A_3}{2}$. The frequencies corresponding to $\frac{A_1}{2} + \frac{A_2}{2}$ and $\frac{A_3}{2}$ are known in this way.

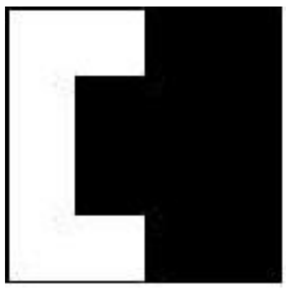
Using the same analysis, we know the frequencies corresponding to $\frac{A_1}{2} + \frac{A_3}{2}$, $\frac{A_2}{2}$, $\frac{A_2}{2} + \frac{A_3}{2}$, $\frac{A_1}{2}$ respectively.

3. While n', n'', n''' are close between each other. With n changing from 10 to 255, adding 1 each time, if $n = n' = n'' = n'''$ occur, Eq. (7) is changed to $\int_0^1 (A_1\cos 2n'\pi t + A_2\cos 2n''\pi t + A_3\cos 2n'''\pi t)\cos 2n\pi t\,dt = \frac{A_1}{2} + \frac{A_2}{2} + \frac{A_3}{2}$, then we obtain the frequency corresponding to $\frac{A_1}{2} + \frac{A_2}{2} + \frac{A_3}{2}$.

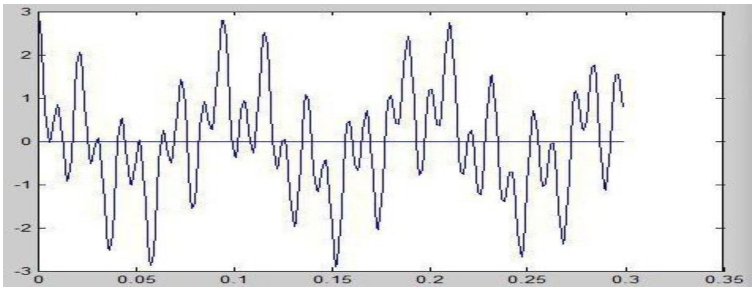
Following the above inner products, we get the frequency feature of each neuron. The neurons with the same frequency are selected, and their corresponding regions are segmented as one objects. The input color image in Fig. 3(1) is segmented following the above algorithm, the corresponding oscillating curves with the same features and the segmented objects are given in Fig. 5.



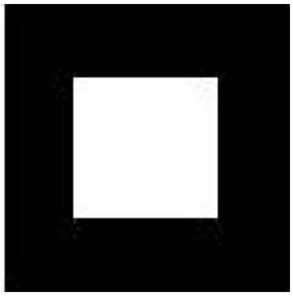
A. The neuron oscillating curve corresponding to object a. in Fig. 3.



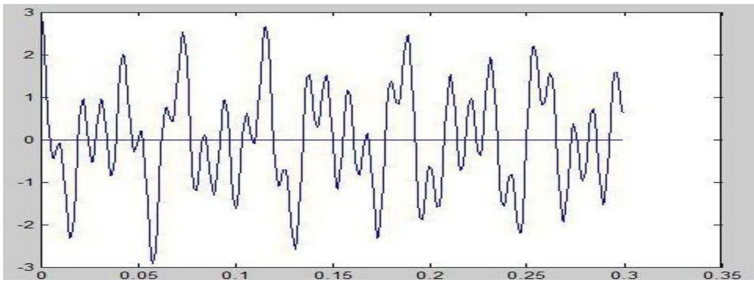
a. The white part denotes the segmented object



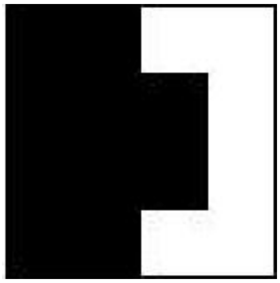
B. The neuron oscillating curve corresponding to object b in Fig.3.



b. The white part denotes the segmented object.



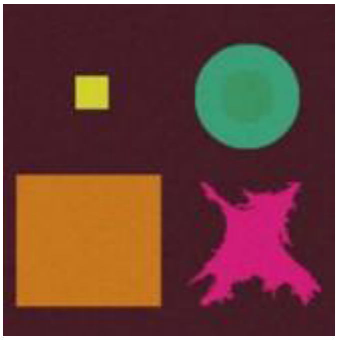
C. The neuron oscillating curve corresponding to object c in Fig.3.



c. The white part denotes the segmented object.

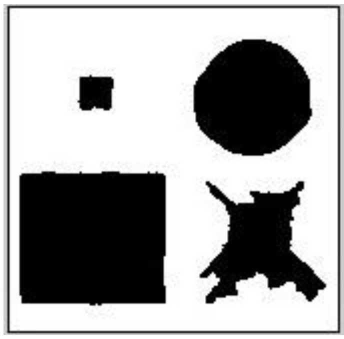
Figure 5: The neuron oscillating curves corresponding to the white areas a, b, c, where the white regions represent the segmented parts with $d_1 = 2$, $d_1 = 6$, $d_1 = 8$ respectively.

Based on the above theoretical analysis, we segment some natural color images using the devised algorithm. The input image is given in Fig. 6(a). Fig. 6(b) gives the segmented square, and (c) shows the segmented background.



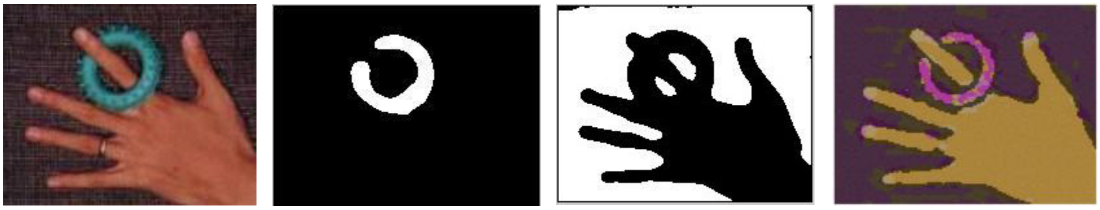
(a) The original input image from reference[15]

(b) The segmented square



(c) The segmented background

Figure 6: Color image segmentation (the white regions represent segmented objects) with $d_1 = 5$, $d_1 = 8$ respectively.



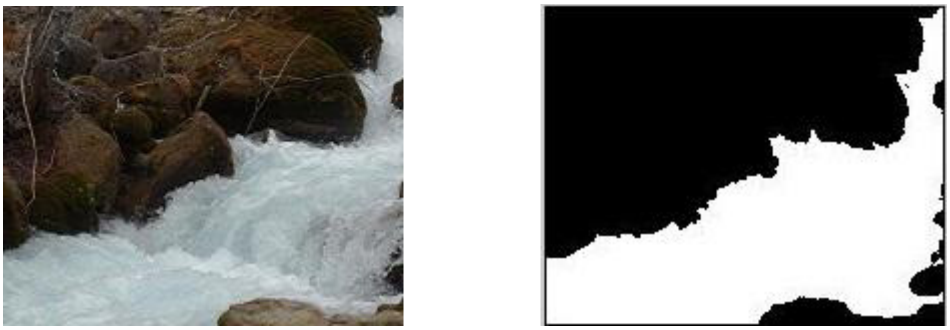
(a) The original input image (b) The segmented ring (c) The segmented background (d) The segmented results from reference [15]

Figure 7: Color image segmentation (the white regions represent segmented objects) with $d_1 = 6$, $d_1 = 10$ respectively.

(a) The original input image (b) Segmented results from reference [16] (c) The segmented results by our proposed algorithm.

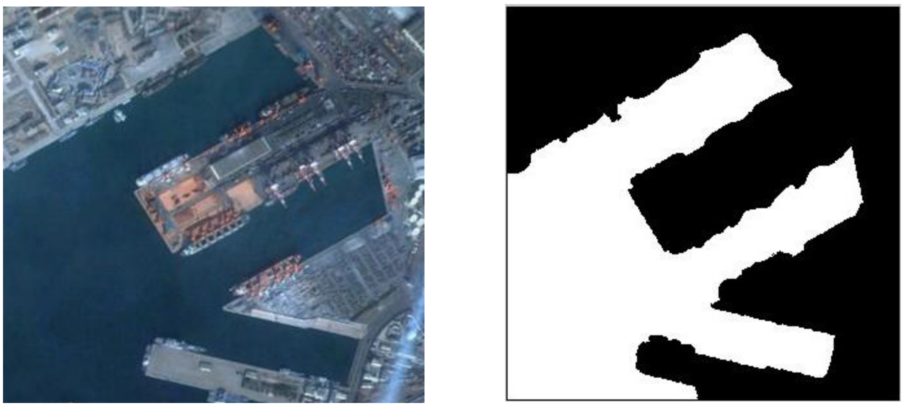
Figure 8: Color image segmentation (the white region represents segmented object) with $d_1 = 5$.

Fig. 7 (a) is another input image. The segmented results are shown in Fig. 7 (b) and (c). Fig.7 (d) gives the segmented results of the approach from reference [16]. It can be seen that the results from our algorithm is a little better than the results from the reference. Fig. 8(c) gives the segmented result of a river by our algorithm, and Fig. 8(b) is the segmented result from reference [16]. As can be seen from Fig. 8, the segmentation from reference [16] is not clear, some parts, especially the top parts of the river, which belong to the river are segmented to other objects, and there are square-like spots in the segmented river. The segmentation of our algorithm is clearer and more precise.



(a) The original input image (b) The segmented rivers

Figure 9: Color image segmentation (the white region represents the segmented object) with $d_1 = 7$.



(a) The original input image (b) The segmented water area

Figure 10: Color image segmentation (the white region represents the segmented object) with $d_1 = 5$.

(a) The original input image (b) The watershed segmentation results [17] (c) The segmented results by our proposed algorithm.

Figure 11: Color image segmentation (the white region represents segmented object) with $d_1 = 5$.

(a) The original input image (b) SVFM results [18] (c) AGM results [19] (d) Results from our algorithm

Figure 12: Color image segmentation (the white region represents segmented object) with $d_1 = 6$.

Fig. 9(a) is a natural color image composed of a river and riversides. We segment the river precisely, and the result is shown in Fig. 9(b). Fig. 10(a) is an image of aerial map, in which the water area is segmented perfectly and the segmentation is shown in Fig. 10(b). Fig. 11(a) is the picture of a starfish. The segmented result is shown in Fig 11(c), and in Fig 11(b) the segmented result from other method [18] is given. It is obvious that the segmentation of our algorithm is much better than that from the reference [18]. Fig. 12(a) gives the picture of a horse and a pony. In Fig. 12(b)(c), the segmentation results from SVFMM [18] and Adaptive Gaussian Mixture Model (AGM) [19] are given. As can be seen from Fig. 12(b) that the pony's head is not clear, and there are many black spots on the segmentation in SVFMM segmentation. It is shown from Fig. 12(c) that the mouth of the horse is not clear. Fig. 12(d) is the segmented results by our algorithm, in which a large part of the segmentation is clear and smooth. However, the part of the hoof is not segmented perfectly. Generally, there are significant advantages of the proposed method in contrast to other approaches.

4 Conclusion

In this paper, we propose a color image segmentation algorithm based on Kuramoto model and oscillation superimposition. Firstly the Kuramoto model is changed from the globally coupled network to the locally coupled network and the coupling pattern is changed from phase coupling to frequency coupling to exclude the phase locked synchronization. Secondly, by defining the instantaneous frequency, we re-build the neuron oscillating activity. Thirdly, by going through the three channel filters, three single gray images corresponding to R, G, B are obtained and the single gray image is put into the frequency coupled network. The oscillating curves for R, G, B are obtained, and the three curves are superimposed for each pixel of the color image. Finally a frequency extraction approach is proposed to identify synchronization. By the synchronization of neuron groups, the color images are segmented.

We segmented a series of natural color images, a large part of the segmentations are precise, and some of the segmentations are perfect. The segment results are compared with some representative methods, and the results from the proposed algorithm are a little better than that from reference [18, 19]. For the segmented result of a river in Fig. 8, our segmentation is much better than that from reference [16]. We also compare the segmentation results with those from SVFMM and Adaptive Gaussian Mixture Model, our segmentation is more clear and smooth, and some parts of the segmentation are more precise.

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